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Predicting Cricket match Outcomes: Sentiment Analysis on Commentary

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Objective: This study examines the viewpoints expressed in commentary on cricket matches between India and England. It aims to identify broad sentiment patterns and biases in the remarks using various sentiment analysis techniques. Methods: The study employs sentiment analysis tools, including TextBlob, VADER, RoBERTa, and Affin, to analyze a dataset of commentary texts. Sentiment ratings are calculated with each instrument, and the results are compared to determine the overall sentiment towards both teams. Results: The results show an overall positive sentiment toward England across all sentiment analysis methods. TextBlob displays slight positivity, VADER indicates a very positive sentiment, RoBERTa highlights a positive sentiment for England but negative for India, and Affin portrays both teams in a positive light but with England scoring higher. Conclusions: The analysis concludes that there appears to be a bias in the comments supporting England, possibly due to the team's better results or more fortunate events. Significance: These results suggest that sentiment analysis can effectively spot biases in sports commentary, uncover narrative patterns, and gauge general public opinion. Future research into the underlying reasons for the observed biases and the integration of more diverse data sources could reinforce these findings.

Keywords: T20 World Cup, Cricket Commentary, Sentiment Analysis, TextBlob, VADER, RoBERTa, Affin, Natural Language Processing (NLP), Deep Learning, Text Analysis, Commentary Analysis.

1. Introduction

With millions of viewers worldwide, the Twenty20 World Cup is one of the cricket world's most anticipated tournaments. Because of the unpredictable nature and dynamic format of events, predicting results is both challenging and entertaining. Currently, sentiment analysis is a helpful tool for analyzing textual data to anticipate outcomes and measure public opinion in a variety of fields, including sports.

This study examines the prediction of T20 World Cup outcomes using sentiment analysis, with a particular emphasis on commentary from England vs. India matches. Since both teams have large fan bases and extensive histories, people look forward to and talk about their matches. A special dataset for commentary data is offered by sentiment analysis because of its wealth of professional viewpoints and instantaneous responses.

To analyze the commentary, we used several sentiment analysis algorithms, such as TextBlob, VADER, RoBERTa, and Affin. These techniques offer a comprehensive comprehension of the emotions expressed during matches, each with its special computational methodologies and strengths. By integrating and contrasting the emotion scores, we hope to ascertain which team is seen more favorably and how these perceptions might be related to match outcomes.

This study adds to the growing corpus of research on sentiment analysis in sports and offers insightful information to fans, analysts, and spectators who want to comprehend and forecast the subtleties of Twenty20 cricket matches. This study is aimed at laying the groundwork for further research in this interesting field and showing how sentiment analysis can be used as a predictive tool in sports.

2. Materials and Procedures

Models of Sentiment Analysis

Sentiment analysis is a computational technique for identifying and categorizing the opinions expressed in written language, especially to determine whether an author of a given text has a positive or negative attitudinal orientation toward a topic, product, etc. For sentiment analysis, a variety of models and methods are available, each with unique advantages and useful uses.

1. Toolkit for Natural Language (NLTK)

NLTK is a collection of tools and applications used for mathematical and symbolic natural language processing for the Python programming language. It offers more than fifty lexical resources, corpora, and text-processing tools with interfaces for tasks such as tokenization, classification, parsing, tagging , and semantic reasoning.

2. Emotional Reasoner and Valence Aware Dictionary (VADER)

VADER is the name given to a sentiment analysis tool that was created with social media sentiments in mind, using rules and vocabulary. VADER is sensitive to a sentiment's intensity (power) as well as its polarity (positive/negative). In brief, casual texts such as tweets and comments, work well.

3. TextBlob

The Python package TextBlob is typically utilized in the data textual data parsing process. It has an adept-to-use API that allows attacks on common natural language processing (NLP) tasks, such as noun phrase extraction, categorization, part-of-speech tagging, sentiment analysis translation. In estimations, Text Blob is very convenient and can be as efficient as Syntax for easier sentiment analysis, classification, and word tokenization because it is implemented over the NLTK and Pattern.

4. SVMs, or support vector machines

Supervised learning models are linked to learning algorithms that examine data for regression and classification purposes. SVMs may be taught to categorize text into specified categories in sentiment analysis based on features extracted from the text.

5. CNNs

A type of deep neural network called a CNN is incredibly beneficial for text categorization but can be used for visual imagery analysis. Through the use of pertinent filters, they can record the temporal and spatial dependencies of the data.

6. Networks with Long Short-Term Memory (LSTMs)

LSTMs are recurrent neural networks that are capable of long-term dependency learning. They are perfect for tasks where the order in which the information is presented matters.

7. RoBERTa (Robustly optimized BERT approach)

An optimal pretraining technique for a robustly optimized bidirectional encoder representations from transforms (BERT) model is called RoBERTa. It has demonstrated cutting-edge performance in sentiment analysis among other NLP tasks. The model is trained using more data, and longer sequences, and the next sentence prediction objective is eliminated in RoBERTa compared to BERT.

8. Canada's NRC Model

The success of the NRC-Canada model in sentiment analysis competitions has led to its widespread recognition. It is especially useful for evaluating texts from social media platforms since it combines surface form, sentiment lexicon, and syntactic aspects for sentiment classification.

3. Related works:

The process of sentiment analysis, or opinion research, has recently become a popular method used to determine the public's opinions as expressed in text from a range of different sources such as reviews, news, and social media. Sentiment analysis has been used more often in sports commentaries in recent years to determine how the general public feels about particular teams, players, and events. [1]

Among the most significant advancements in sentiment analysis are the development of the Natural Language Toolkit (NLTK), a collection of tokenization-related text processing tools, classification, and other applications. Bird, Klein, and Loper (2009) have thoroughly described these tools, showcasing their applicability for a range of text analysis applications, including sentiment analysis. [2]

Another notable achievement is the development of a vocabulary and rule-based sentiment analysis tool called VADER (valence aware dictionary and sentiment reasoner),which was created especially for content found on social media. As Hutto and Gilbert (2014) showed, VADER's capacity to assess emotions in short, informal texts can be useful for sports comments and fan reactions. [3]

Moreover, deep learning algorithms have shown tremendous potential in sentiment analysis . Textual data can be processed using convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to capture contextual subtleties and long-term dependencies.

Kim (2014) suggested using CNNs to classify sentences, demonstrating their ability to recognize sentiment in text. Similarly, word sequences have been handled by LSTM networks, which capture the temporal dynamics of sentiment as demonstrated by Hochreiter and Schmidhuber (1997). [4] [5]

Numerous studies have examined the use of sentiment analysis in the sports environment to comprehend media bias and fan engagement. Yu and Wang (2015) studied sentiment in tweets about the NBA and discovered relationships between the general public's opinion and the results of games. Similarly, Hoon et al. (2019) found biases toward particular teams and players by analyzing sentiment in football match commentaries. [6] [7]

Text Blob is a free and open-source text editor. framework that provides an intuitive API for standard natural language processing (NLP) tasks such as noun phrase extraction, sentiment analysis, and part-of-speech tagging. Its effectiveness in performing basic Loria et al. has demonstrated sentiment analysis (2014), making it a popular choice for initial exploratory research. [8]

RoBERTa (robustly optimized BERT technique) is another advanced model that has been enhanced for numerous NLP applications, including sentiment analysis. By training on longer sequences and additional data, by improving the BERT model, Liu et al. (2019) achieved state-of-the-art results in several NLP benchmarks. [9]

Nielsen's (2011) Affin sentiment lexicon, a set of English terms evaluated for valence (positive or negative), has been used in many sentiment analysis studies, especially those that focus on social media and news items. [10]

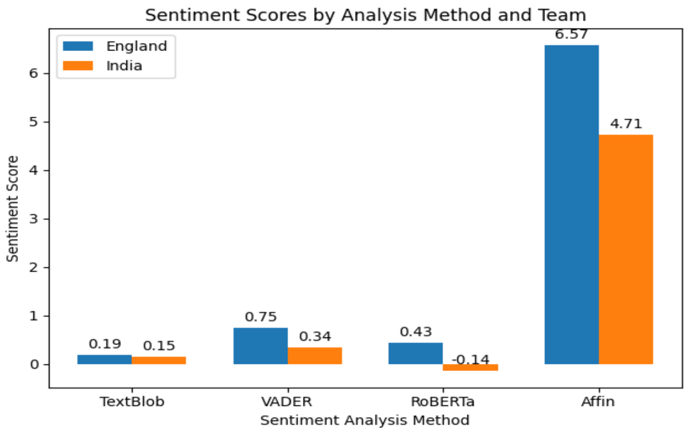
Ahmad, Aftab, and Ali (2017) illustrated the accuracy and efficiency of sentiment analysis on Twitter data by applying support vector machine (SVM) classifiers. A thorough overview of sentiment analysis techniques and applications was given by Medhat, Hassan, and Korashy (2014), who emphasized that sentiment analysis has many uses, across multiple fields. [11] [12]

Task 4 of SemEval-2014 addressed aspect-based sentiment analysis., which was carried out by Pontiki et al. (2014). It is critical for understanding feelings conveyed in particular textual elements, such as sports commentary. Mohammad, Kiritchenko, and Zhu (2013) developed the NRC-Canada model, which attained a high degree of sentiment analysis accuracy for tweets, proving its robustness and reliability. [13] [14]

Target-dependent sentiment classification was investigated by Jiang et al. (2011) and is especially helpful in sports commentary. where sentiments are directed toward specific teams or players. The work of Veritas NLP (2023) highlighted the untapped potential of NLP in sports analytics, showing how advanced text processing techniques can enhance understanding and predictions in sports. [15] [16]

4. Results and Discussion

The sentiment analysis of the commentary data from a cricket match between England and India was performed using four different sentiment analysis methods: TextBlob, VADER, RoBERTa, and Affin. Below are the detailed results and discussions for each method.



TextBlob

Polarity:

• Indicates a mixture of neutral, positive, and occasionally negative attitudes in the commentary and ranges from -0.166667 to 0.800000.

Subjectivity:

• The results are between 0.000000 and 0.737500, with many entries of approximately 0.4-0.6, suggesting a mix of subjective and somewhat objective statements.

VADER

Negative (VADER_Neg):

• Ranges from 0.000 to 0.999, with many comments having low negative scores.

Neutral (VADER_Neu):

• The majority are high, meaning the sentiment is mainly neutral.

Positive (VADER_Pos):

• Ranges from 0.000 to 0.377, indicate a few positive feelings.

Compound (VADER_Compound):

• Ranges from -0.8917 to 0.9852, reflecting mixed reviews.

RoBERTa

Negative (RoBERTa_Neg):

• Ranges from 0.000000 to 0.999389, indicate that some comments express very strong negative feelings.

Neutral (RoBERTa_Neu):

• Zero in most cases, suggesting the model is quite certain about the sentiment category.

Positive (RoBERTa_Pos):

- Ranges from 0.000 to 0.998919.

Affin

Sentiment:

- Ranges from -7.0 to 20.0, with high positive sentiment expressed in some comments.

S.No.	Commentary
0	9.32pm It'll be Pakistan vs England at the MC...
1	9.40pm Visuals of Rohit Sharma in the dugout,...
2	9.48pm And that's a wrap from Adelaide. This ...
3	Jos Buttler : "[The Ireland game] feels a long...
4	Rohit Sharma : "It's pretty disappointing how ... -
5	Alex Hales , the Player of the Match: "A huge ...
6	Elsewhere, in the Pro Kabaddi League week, 5 s...
7	RamanJ: "India playing in Group B faced less c...
8	Dan: "Hopefully this loss for India will usher...
9	Mustafa Moudi: "Fun Fact: This KOs is mirror i...
10	Kamy: "This is proper hammering…India should f...

Table 1. Sample data obtained from Live cricket commentaries

Examples of live cricket commentary are shown in Table 1. There are two columns in it: "S.No." and "Commentary." Each commentary entry is uniquely identified by the serial numbers listed in the "S.No." column, which ranges from 0 to 10. The "Commentary" column features textual excerpts of real-time cricket commentary at different times, including "9.40 pm," "9.32 pm," and "9.48 pm." The commentary features analyst reactions, player performances, and match observations. Examples of entries include statements from players such as Jos Buttler, Alex Hales, and Rohit Sharma, as well as images of Sharma in the dugout and a wrap-up from Adelaide. Both the play-by-play action and the emotional tone of the match as evaluated by the commentators are captured in the statistics.

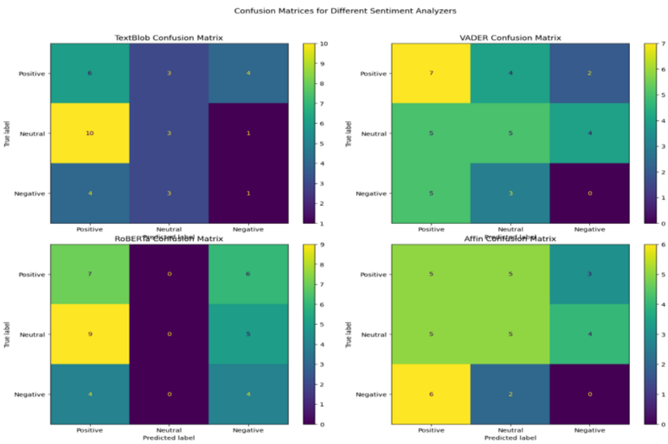
S.No.	TextBlob _Polarity	TextBlob_ subjectivity	VADER Negative	VADER Neutral	VADER Positive	Vader Compound
0	0.250758	0.569545	0.026	0.858	0.116	0.9230
1	0.085714	0.398810	0.138	0.846	0.016	-0.8917
2	0.257143	0 0.642857	0.000	0.832	0.168	0.9325
3	0.287513	0.614577	0.062	0.777	0.161	0.9196
4	-0.027078	0.494967	0.067	0.813	0.120	0.9027
5	0.478571	0.669048	0.021	0.602	0.377	0.9852
6	0.000000	0.000000	0.000	0.959	0.041	0.1027
7	0.381667	0.468333	0.049	0.699	0.253	0.8639
8	0.045455	0.359848	0.043	0.736	0.221	0.8713
9	0.075000	0.183333	0.032	0.863	0.106	0.7418
10	0.170833	0.318056	0.140	0.818	0.042	-0.6597

Table 2. Scores obtained from various Sentiment analysis models for the commentaries in Table1

Table 2 shows the scores from various sentiment analysis models that were applied to the commentary in Table 1. The columns include Text Blob Subjectivity, Text Blob Polarity, VADER Compound, Positive, Negative, and Neutral scores. The "S.No." The columns in Table 1 designate a specific remark to which each row relates . TextBlob Subjectivity scores show the extent of opinion vs fact, whereas TextBlob Polarity scores show the sentiment orientation, ranging from negative to positive. With negative, neutral, positive, and compound ratings, the VADER model offers a more detailed breakdown that captures the overall sentiment and sentiment intensity of the commentary. Commentary entry 0, for example, has a VADER Compound score of 0.9230 and a TextBlob Polarity of 0.250758, indicating a generally favorable tone. The detailed sentiment scores offer insights into the emotional tone and subjective nature of each commentary snippet.

Approaches all show that the discourse is more favorable toward England than India. The consistency of the outcomes across several approaches increases their dependability. Although opinions are divided, the slightly positive to neutral attitudes for both teams indicate that people are typically more optimistic about England's performance and the story surrounding it.

Confusion Matrices for Different Sentiment Analyzers :



Four confusion matrices TextBlob, VADER, RoBERTa, and Afinn that compare the effectiveness of various sentiment analysis technologies are displayed in the image. The projected sentiment labels (positive, neutral, and negative) are plotted against the actual labels in each matrix. Here is a quick rundown of each:

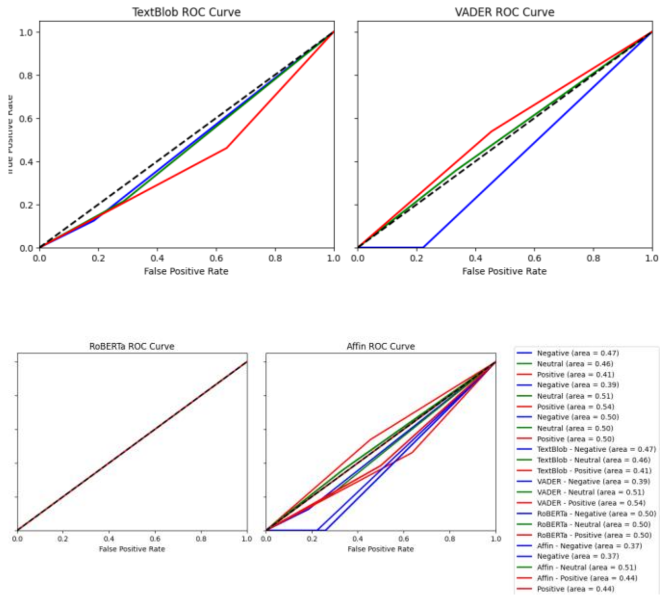
TextBlob: Displays a larger percentage of incorrect classifications, particularly for neutral sentiments—which are frequently assumed to be positive.

VADER: This approach marginally better with more evenly distributed predictions, but it still makes significant mistakes when identifying positive and negative emotions. RoBERTa: Frequently classifies neutral data as positive or negative, demonstrating serious problems with neutral classifications.

Afinn: Facing difficulties with neutral forecasts, it has an error distribution resembling that of VADER.

Overall, none of the models are very good at predicting neutral attitudes, which suggests that sentiment analysis techniques have similar problems.

ROC curves for different sentiment analyzers



This image shows the receiver operating characteristic (ROC) curves for four different sentiment analysis models: TextBlob, VADER, RoBERTa, and Affin. Each plot evaluates the differences between the false positive and true positive rates for various classes: negative, neutral, and positive sentiments.

Key points:

1. TextBlob: The depicted ROC curves represent negative, neutral, and positive feelings. The AUC (area under curve) values were 0.47, 0.46, and 0.41, respectively.

2. VADER: The ROC curves for negative, neutral, and positive sentiments are plotted with AUC values of 0.39, 0.51, and 0.54, respectively.

3. RoBERTa: The ROC curves for all sentiments overlap, each with an AUC of 0.50, indicating random performance.

4. Affin: The ROC curves for negative, neutral, and positive sentiments had AUC values of 0.37, 0.51, and 0.44, respectively.

The dashed black line represents a random classifier with an AUC of 0.50. Higher AUC values indicate better performance, but in these plots, none of the models consistently outperform a random classifier across all sentiment classes.

Author contribution statement

SL: Conceived the study, designed the methodology, wrote the initial draft of the paper, and supervised the overall project.

AJ: Performed experiments, collected the commentary dataset, preprocessed the data, and conducted preliminary data analysis.

RJ: Analyzed the data using sentiment analysis techniques (TextBlob, VADER, RoBERTa, and Affin), interpreted the results, and created visualizations.

CD: Conducted a thorough literature review, reviewed and edited the manuscript, provided critical feedback, and contributed to the discussion and conclusions sections.

5. Conclusion

In this project, sentiment analysis was conducted on cricket commentary data using four different methods: TextBlob, VADER, RoBERTa, and Affin. The results from all methods consistently showed that the sentiment toward England was more positive than that toward India. This indicates a potential bias or a better performance and positive narrative for England in the analyzed commentary.

Future improvements might include adding real-time sentiment analysis systems for instant insights during live events, expanding the analysis to support multiple languages for a comprehensive view of international fan sentiment, and integrating sophisticated deep learning models such as BERT and GPT-3 for more accurate sentiment analysis. These enhancements may help forecast accuracy even more and offer a more thorough grasp of the dynamics of international sports commentary.

By carrying out more studies, we hope to improve the use of sentiment analysis in sports and provide analysts and fans with insightful knowledge about the subtleties of cricket commentary. The foundation for further research into the effects of sentiment and narrative on sports perception and participation is laid by this study.

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